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GGDC RESEARCH MEMORANDUM *142*

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August 2013

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August 2013

ABSTRACT

Employment protection affects aggregate productivity via several channels in potentially contradicting ways, which makes it difficult to establish the relationship between the two. This study focuses on the misallocation of production factors across plants, which has been shown in past studies to substantially reduce aggregate productivity. The study provides new evidence on the effect of employment protection on resource misallocation using a large dataset of manufacturing plants covering more than 90 countries. For measuring misallocation, I use the within-industry dispersion of the marginal product of labor and total factor productivity. The results show that higher cost of dismissing redundant workers is positively associated with misallocation. The effect of dismissal cost is especially larger in industries that have greater demand for adjusting labor. More specifically, the effect is larger in industries that intrinsically have higher layoff rate, and in industries that have large positive or negative sales growth rates.

JEL Classification: O40, J08, L60, D24

Key Words: Misallocation, Employment protection, Aggregate productivity

1. INTRODUCTION

Although the effect of employment protection on aggregate productivity is getting increasing attention (Bassanini *et al*, 2009), establishing the relationship between the two is difficult for many reasons. An important challenge stems from the fact that employment protection affects aggregate productivity via two different channels that are potentially contradicting. Firstly, employment protection affects technological change and technical efficiency by influencing the incentive of the firm to invest in new technologies and on the motivation of workers to learn new production techniques. The relationship in this regard is unclear since both theoretical and empirical evidence shows that the effect of employment protection on innovation and worker motivation is ambiguous[1]. Secondly, employment protection induces misallocation by distorting the process of labor reallocation across plants, ultimately reducing aggregate productivity. The majority of existing studies do not distinguish between these two separate effects since they rely on aggregate productivity data.

This paper focuses exclusively on the effects of employment protection on resource misallocation across plants. An emerging literature, recently reviewed by Restuccia and Rogerson (2013) in a special release of the *Review of Economic Dynamics*, asserts that misallocation of factors of production substantially reduces aggregate productivity. An influential paper by Hsieh and Klenow (2009) documents the presence of significant within-industry dispersions in the marginal products of labor and capital in China and India. This dispersion is relatively lower in the US, implying that distorting policies and institutions in China and India induce resource misallocation across plants. Restuccia and Rogerson (2008) use a growth model to show that misallocation of resources across heterogeneous plants can substantially lower aggregate productivity. These and other recent studies (Alfaro *et al*, 2009; Bartelsman *et al*, 2013; Kamal and Lovely, 2012) underscore the need to understand the sources of resource misallocation across plants is order to explain productivity differences across industries and countries.

Theoretical models show that employment protection can induce resource misallocation by reducing the ability of firms to adjust their labor in response to demand and technological shocks. Hopenhayn and Rogerson (1993) show that, by creating a wedge between the marginal product and marginal cost of labor, dismissal cost reduces employment and lowers labor

[1] Belot *et al* (2002) argue for a positive effect of employment protection on worker motivation whereas Ichino and Riphahn (2005) provide evidence to the contrary. The evidence regarding innovation is similarly mixed. Bartelsman *et al* (2010) suggest that employment protection could discourage firms from investing on high-risk technologies and Saint-Paul (2002) also shows that countries with rigid labor regulation will specialize in non-innovative products. On the other hand, Koeniger (2005) argues that high dismissal cost pushes incumbents to innovate and increase productivity in the short run in order to avoid costly labor adjustments.

productivity. Lagos (2006) similarly demonstrates how higher dismissal cost can reduce aggregate productivity[2]. Several empirical studies also document the negative effect of employment protection on job flows and worker reallocation (Haltiwanger *et al*, 2008; Kugler and Pica, 2008; Micco and Pagés, 2006; Martin and Scarpetta, 2012).

In spite of the clear theoretical prediction, there is limited empirical evidence on the effect of employment protection on resource misallocation across plants. The main contribution of this paper is providing the first empirical evidence on the effect of employment protection on resource misallocation across plants in several countries[3]. Misallocation is measured using the dispersion (standard deviation and interquartile range) of the marginal product of labor and total factor revenue productivity across plants within an industry. Theoretical studies have indicated that the dispersion of marginal products and productivity can be used as summary measures for the level of misallocation across plants (Hsieh and Klenow, 2009). Greater dispersion of productivity and marginal products in an industry implies substantial unrealized gain in aggregate productivity caused by the failure to reallocate resources from less productive to more productive firms (Ito and Lechevalier 2009; Syversson, 2004).

The analysis in this paper is based on data from the World Bank's Enterprise Surveys (WBES) dataset, which provides detailed plant-level data for several countries that is collected using standardized survey instruments. The dataset used for analysis in this paper covers close to 30,000 manufacturing plants in 91 countries. The industry-level measures of dispersion that are computed from the plant-level WBES dataset are then combined with country-level dismissal cost data from the World Bank's Employing Workers dataset, which is also extensive in its country coverage. Dismissal cost is measured in standardized form as the number of weeks of salary that employers are required to pay as severance payment upon dismissing redundant workers.

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[2] Some theoretical studies look into the interactions between employment protection and other institutions. Kambourov (2009) uses a general equilibrium model to show how employment protection slows down the inter-sectoral reallocation of labor after a trade reform. Boedo and Mukoyama (2012) show that differences in dismissal cost and entry restrictions are important in explaining cross-country differences in aggregate productivity. Poschke (2009) studies how employment protection lowers productivity by reducing labor reallocation and firm exit. Garicano *et al* (2012) find that size contingent employment protection lowers output in France.

[3]Using aggregated, industry-level data for several countries, Caballero *et al* (2013) find that employment protection leads to greater deviations from optimal labor use. However, their measure of deviation from optimal employment is not specifically related to misallocation across plants, and does not have a clear link with aggregate productivity. In contrast, this paper studies misallocation of resources across heterogeneous plants, which has a clear link with aggregate productivity. Other studies look into the effects of employment protection on labor adjustment in a single country (Eslava *et al*, 2004; Petrin and Sivadasan, 2013).

A related contribution of this paper is related to the uniquely extensive coverage of the WBES and Employing Workers datasets. Due to lack of comparable data for employment protections and productivity, the focus of the existent literature is largely confined to OECD countries, which limits the generalizability of the evidence (Caballero *et al*, 2013). In contrast, the dataset used in this paper covers a large number of developed and developing economies, which exhibit great variation in the level of employment protection. The large country coverage of this dataset makes it possible to exploit the great cross-country variation in dismissal cost to explain misallocation.

The results show that dismissal cost has a significant positive effect on misallocation after several confounding institutional factors such as the level of competition and financial development are controlled for. In order to identify the channel through which employment protection affects misallocation, I test if the effect of employment protection is higher in industries with greater demand for labor adjustment. First, I use inherent differences across industries in terms of layoff rate due to technological and demand structures as a measure of labor adjustment demand (as in other studies such as Bassanini *et al*, 2009 and Cingano *et al*, 2010). Using difference-in-difference estimation strategy, I show that the effect of employment protection on misallocation is significantly higher in industries with higher layoff rate. In addition, I find that employment protection increases misallocation significantly more in industries with large positive or negative sales growth rates, revealing that its effect is bigger in dynamic industries with greater labor adjustment demand. These results conform to the view that employment protection imposes an institutional adjustment cost that reduces the reallocation of resources across plants. The results are robust to multiple sensitivity tests including instrumental variable estimation, using alternative proxies of labor adjustment demand, controlling for various aspects of employment protection, and using alternative measures of misallocation.

The rest of the paper is organized as follows. Section 2 describes the empirical methodology including the measurement of misallocation and the regression framework. Section 3 discusses data and measurement issues, and provides descriptive results for the measures of misallocation and employment protection. Section 4 provides the baseline regression results. Section 5 presents a number of sensitivity tests and section 6 concludes the paper.

2. EMPIRICAL METHODOLOGY

This section introduces the measures of misallocation and describes the empirical methodology used for testing the effect of employment protection on misallocation.

2.1. Measures of misallocation

This sub-section motivates the use of dispersions of the marginal (revenue) product of labor (MPL) and total factor productivity of revenue (TFPR) as indicators of misallocation of resources across plants. The main analysis in the paper is based on the standard deviations of the logs of MPL and TFPR across plants within industries. However, I also conduct robustness tests using the interquartile range, which is less sensitive to outliers.

Assuming a price-taking firm with Cobb-Douglas production technology, the marginal (revenue) product of labor (MPL), is defined as follows:

(1) $$MPL \equiv p\left(\frac{\partial Q}{\partial L}\right) = \beta p\left(\frac{Q}{L}\right) \quad ,$$

where p is output price, Q is quantity of output, L is labor input, and β is the output elasticity of labor that varies across industries and countries but is the same for plants within the same industry[4].

Previous studies have looked into differences in MPL that are measured under these assumptions to impute implicit distortions that induce misallocation (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Kamal and Lovely, 2012). Compared to the market wage rate, larger values of MPL reveal that the firm is under-employing labor whereas smaller values indicate that the firm is overemploying labor. Large dispersion in the marginal product of labor across plants thus imply significant unrealized gain in output caused by the failure to reallocate labor from plants with smaller marginal products to those with higher marginal products.

In the spirit of the misallocation literature, I interpret within industry dispersions in the marginal product of labor as results of misallocation. In Hsieh and Klenow (2009), for example, any deviation from the average wage rate ($\overline{w}$) is modeled as an outcome of market distortions.

[4] Our measures of dispersion are unaffected if we make the alternative assumption that firms operates in a monopolistic market as is often done in the misallocation literature (Hsieh and Klenow, 2009). If firms face a demand curve with a constant elastcity, MPL takes the following form: $MPL \equiv \frac{\partial(P*Q)}{\partial L} = (1+\sigma^{-1})\beta\frac{PQ}{L}$ where $\sigma = (\partial Q/\partial P)P/Q < -1$ is the price elasticity of demand. Since MPL in Equation 1 is a constant fraction of the MPL of a monopolistic firm, dispersions based on the log forms of both measures of MPL will be identical.

Hence $MPL_i \equiv \beta p(Q_i/L_i) = \overline{w}(1+\tau_i)$ where τ_i is the idiosyncratic distortion firm *i* is facing, which can be further decomposed into sub-components. Larger marginal products thus imply larger distortions that lower firm size. For example, Hsieh and Klenow (2009) and Kamal and Lovely (2012) report that state owned enterprises in China have lower marginal products of labor, implying that they get implicit labor subsidy.

In the current setting, τ_i can be considered an outcome of a random exogenous productivity or demand shock that pushes the firm's marginal product above or below the market wage rate. It is possible to re-write the above equation as $MPL_i/(1+\tau_i) = \overline{w}$ and re-define $\tau_i > -1$ as demand shock. In a frictionless market, a firm with a positive realization of demand shock will respond by hiring additional workers until its marginal product falls to the level of the market wage rate, and vice versa. After all firms readjust their labor, marginal products become equal to the wage rate so that there are no dispersions of marginal products. If labor adjustment costs are high relative to the shock, certain firms could find it unprofitable to adjust their labor inputs. For example, high dismissal cost could force a firm facing a negative realization of demand shock to keep its workers although their MPL has fallen below the wage rate. The higher the dismissal cost, the smaller becomes the proportion of firms that will find it profitable to fire redundant workers, and hence the greater the dispersion in observed marginal products. Other things constant, an industry in which labor adjustment cost is higher will have a greater dispersion of marginal products[5].

Besides affecting the allocation of labor, employment protection can also have an additional effect of inducing capital misallocation in so far as capital and labor are substitutes. Therefore, I use the dispersion of total factor productivity, which also captures misallocation of capital, as a second measure of misallocation. Under Cobb-Douglas technology and constant returns to scale assumption, revenue productivity is defined as follows:

$$(2) \qquad TFPR \equiv \frac{pQ}{L^{\beta}K^{1-\beta}} \quad ,$$

where K is capital stock.

[5] In reality, dispersions in marginal products could arise for a number of other reasons than institutions that raise adjustment costs. Even in competitive markets such as the US economy, studies document substantial dispersion of marginal products and productivity (Syverson, 2011; Foster *et al*, 2001). Apart from data and measurement problems, this shows that non-policy factors such as sunk costs, market power, and the process of learning-by-doing among new entrants could induce productivity dispersions (Syverson, 2004). However, an important thesis in the misallocation literature is that, in spite of these differences, higher dispersions in marginal products are associated with greater market distortions that induce misallocation (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008).

Although I simply refer to it as productivity, TFPR is different from physical productivity since revenues are used to measure output rather than physical output. Hence TFPR is the product of output prices and physical productivity. Hsieh and Klenow (2009) show that, in a monopolistic competition setting, the firm's TFPR is proportional to the geometric mean of its marginal products of labor and capital. Therefore, TFPR captures distortions that affect the marginal products of both capital and labor, which makes it a composite measure of input misallocation. Intuitively, large values of TFPR imply that the firm is unable to increase its output due to distortions that affect its ability to increase its inputs. Therefore, high dispersions of TFPR reflect arbitrary distortions that lead to substantial misallocation of inputs. Hsieh and Klenow (2009) also provide a framework that shows how misallocation, measured as the variance of TFPR, has a negative effect on aggregate productivity.

2.2. Regression framework

Existing studies analyze the effect of employment protection on productivity using aggregate industry-level data and firm-level data, mostly from OECD countries. Among the studies that rely on aggregate data, Bassanini *et al* (2009) document the negative effect of dismissal regulation on productivity growth using industry-level panel data of OECD countries. Besley and Burgess (2004) find that pro-worker employment protection legislations are associated with lower output, employment, investment, and productivity in formal manufacturing across Indian states. The obvious disadvantage of using aggregate data is that it masks the effect of employment protection both on technological change and on misallocation across plants. The results are thus difficult to interpret, especially given the possibility that employment protection could positively affect innovation or workers' productivity.

Studies that use micro-level data, on the other hand, can directly test the effect of employment protection on firm productivity and job flows. Cingano *et al* (2010) show that employment protection reduces value added per worker and investment among European manufacturing firms. They also find that dismissal regulations lower productivity growth in industries where layoff restrictions are more likely to be binding. Autor (2006) shows that the adoption of restrictive employment laws in US states had a negative effect on job flows and productivity among firms. While these micro-based studies can uncover how employment protection affects firm productivity, they disregard its effect of inducing misallocation across plants[6].

[6] An exception in this regard is the literature that documents the negative effect of employment protection on job flows and worker reallocation (Haltiwanger *et al*, 2008; Kugler and Pica, 2008; Micco and Pagés, 2006; Martin and Scarpetta, 2012). In spite of its focus on labor allocation, this literature is principally descriptive since there is no clear-cut theoretical link between job flows and aggregate productivity. Moreover, these studies are largely confined to a few OECD countries.

This paper, in contrast, focuses on misallocation of resources across plants that have clear theoretical link with aggregate productivity. Due to the extensive country coverage of the plant-level WBES dataset, within-industry measures of dispersion can be calculated for a large number of countries. This allows us to investigate the effect of cross-country differences in employment protection on misallocation using country-industry data. I use the following cross-sectional empirical methodology:

(3) $MIS_{jc} = \alpha(EP_c) + \eta(X_c) + \theta(D_j) + \varepsilon_{jc}$,

where the subscripts *j* and *c* are industry and country indices respectively. *MIS* refers to misallocation, measured as the within-industry dispersion of MPL or TFPR. *EP* is employment protection, in this case the cost of dismissing redundant workers. The vector *X* includes a set of country-level control variables that are discussed in the following sub-section. The vector *D* denotes industry dummies that capture industry-specific demand and technological differences that can potentially affect the dispersion of marginal products. These include, for example, fixed entry costs that reduce competition, or the level of product differentiation that gives firms market power (Syverson, 2004).

If higher dismissal cost slows down the allocation of workers from less productive to more firms, other things constant, this leads to greater dispersion of marginal products and productivity. Therefore, the coefficient of interest, α, is expected to have positive sign.

Equation (3) is useful for estimating to what extent employment protection affects misallocation. However, it is not informative regarding the specific channel through which this effect is realized. Therefore, I consider an interaction effects model in order to test the hypothesis that employment protection induces misallocation by increasing the cost of labor adjustment. If the hypothesis is true and employment imposes an 'institutional' cost for adjusting labor, its effect will be larger in industries with greater demand for labor adjustment. In this paper, I consider two sources of differences in labor adjustment demand among industries.

Firstly, I look into exogenous differences among industries in their demand for adjusting their labor inputs. Studies have shown that there are systematic and significant differences across industries in their demand for labor adjustment measured in terms of job flow rate, worker reallocation and layoff rate. The ranking of industries based on these measures is also consistent across countries (Haltiwanger *et al*, 2008; Micco and Pagés, 2006). The potential reasons for this empirical regularity could be differences in technological structure, the nature of demand shocks, and variations in size among firms (Haltiwanger *et al*, 2008). For example, the nature of demand in some industries could entail larger demand volatility, whereas the technological structure may determine the necessary level of specialization of workers or the substitutability of different worker types. These and other factors could induce differences in the ease with which labor can be adjusted across industries[7].

In this paper, I follow Bassanini *et al* (2009) and use the concept of *layoff propensity* which gauges the extent to which industries depend on layoffs to adjust their labor[8]. To test if dismissal cost has larger effect on industries with higher layoff rate, I estimate the following regression model:

$$(4) \quad MIS_{jc} = \beta\left(EP_c * LAYOFF_j\right) + \theta\left(D_j\right) + \lambda(D_c) + \varepsilon_{jc} \ ,$$

where *LAYOFF* is the benchmark layoff propensity that varies across industries, but not across countries. D_j and D_c are respectively vectors of industry- and country-effects dummies. Since industries with higher layoff propensity will be most affected by employment protection, the expected sign of β in the regression model for the interaction effect of layoff propensity is positive.

Equation (4) is the standard difference-in-difference estimation strategy that exploits variations across industries and countries while removing all differences across industries and countries through the inclusion of dummy variables. Given multiple sources of institutional heterogeneity across countries, the inclusion of country effects is an important step for reducing potential omitted variable problems.

As a benchmark for layoff propensity, I use the average percentage ratio of annual layoffs to total employment in US industries, which is taken from Bassanini *et al* (2009). This variable is measured at the level of 2-digit ISIC codes, and is expected to capture inherent differences in reliance on layoffs across industries. Since the US has the least restrictive employment protection legislation, US data is believed to reflect inherent industrial features better than data from other countries. Bassanini *et al* (2009) argue that industry rankings by layoff rate are consistent across countries and over time, implying that differences in layoff rate are inherently exogenous. For sensitivity test, I also use a binary form of US layoff rate and alternative layoff rate taken from UK data.

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[7] For example, textile industries experience frequent demand shocks due to changes in fashion and preferences, which could increase their demand for labor adjustment (Micco and Pagés, 2006).

[8] Bassanini *et al* (2009) argue that *layoff propensity* is the most relevant proxy of labor adjustment demand compared to other alternatives such as workflows and employment turnover because it has a direct relation to dismissal cost. They find that dismissal cost has significantly larger negative effect on productivity growth in industries that have higher *layoff propensity*. A number of studies also document that employment protection has greater effect on the performance of industries with inherently greater labor adjustment demand (Micco and Pagés, 2006 and Cingano *et al*, 2010).

In addition to layoff propensity, I also consider labor adjustment demand differences induced by output growth. Industries that are growing fast are likely to have greater need for hiring workers, and hence to be affected significantly more by employment protection. Since sales growth varies significantly across countries and industries, it offers a source of variation that can be used for testing the effect of employment protection on misallocation[9].

However, the relationship between labor adjustment demand and sales growth is not linear since sales growth can be positive or negative. Demand for labor adjustment is high when sales growth is large and positive (i.e. when the industry is booming) and when it is large and negative (i.e. when the industry is shrinking). Therefore, the effect of employment protection on misallocation is expected to be higher in expanding and shrinking industries. I use the following specification to test this hypothesis:

$$(5)\quad MIS_{jc} = \beta\left(EP_c * GROWTH_{jc}{}^2\right) + \gamma\left(EP_c * GROWTH_{jc}\right) + \delta\left(GROWTH_{jc}{}^2\right) + \eta\left(GROWTH_{jc}\right) + \theta\left(D_j\right) + \lambda(D_c) + \varepsilon_{jc}\,,$$

where $GROWTH_{jc}$ is the rate of sales growth rate in industry *j* and country *c.*

The interaction term between the measure of employment protection and the square of sales growth reflects the non-linear relationship between sales growth and labor adjustment. The coefficient of interest, β, is expected to be positive implying a U-shaped relationship between sales growth and the marginal effect of employment protection. Given that labor adjustment demand is high in expanding and shrinking industries, the marginal effect of employment protection is expected to be higher in industries with large positive and negative sales growth rates. Note that both sales growth and its squared term are included to capture their direct effect on misallocation.

For estimating Equation (5), I use sales growth rate at country-industry level from the INDSTAT database (UNIDO, 2012). This variable is the best proxy for labor adjustment demand due to output expansion within an industry. Unfortunately, detailed industry data is available for relatively small number of countries, considerably reducing the number of observations available for analysis. Therefore, I check the sensitivity of the results using alternative proxies

[9] Since sales growth and sales volatility are positively correlated across industries (Imbs, 2007), this approach is equivalent to testing the hypothesis that industries with greater sales volatility are affected more by employment protection. Micco and Pagés (2006) show that employment protection reduces job reallocation significantly more in industries with high sales volatility since a larger share of firms have labor adjustment demand in these industries. Cuñat and Melitz (2012) use the same notion to show that countries with more flexible labor markets are more likely to specialize in sectors that exhibit greater demand volatility.

such as the proportion of plants within each country-industry that reported sales growth and the average size of industries.

2.3. Control variables

In order to isolate the effect of employment protection on misallocation in Equation (3), it is necessary to control for a number of institutional factors that could affect misallocation. This sub-section briefly discusses four institutional factors with such an effect.

i. Barriers to external competition. Exposure to external competition because of openness to trade and foreign direct investment can enhance allocative efficiency. As highlighted by the seminal work of Melitz (2003) trade openness intensifies competition and increases aggregate productivity by allowing more productive firms to expand and the least efficient firms to exit. There is also an extensive empirical literature supporting the reallocative effect of trade and FDI. In this paper, trade openness is measured using trade intensity, calculated as imports plus exports in real prices expressed as a percentage of GDP using data from the Penn World Tables dataset (Feenstra *et al*, 2013). In addition, I control for net FDI inflows as a percentage of GDP, taken from the World Development Indicators database.

ii. Barriers to domestic competition. Regulatory constraints that discourage the entry of new firms can exacerbate misallocation. A large literature studies the economic consequences of regulatory entry barriers in the form of high registration costs and licensing restrictions (Djankov *et al*, Boedo and Mukoyama, 2012). As a measure of entry barriers, I use the number of procedures that newly entering firms have to complete in order to register officially. This indicator was originally developed and used as a proxy of entry regulation by Djankov *et al* (2002).

iii. Financial frictions. Financial frictions are among the most widely studied determinants of misallocation (Restuccia and Rogerson, 2013). The level of financial development in a market can affect allocative efficiency in two ways. Firstly, efficient financial intermediation increases firm entry by lowering the cost of financial capital, thus intensifying competition and forcing inefficient incumbents to exit. Secondly, well-developed financial markets are more capable at identifying profitable firms and reallocating capital towards them, thus reducing misallocation. To control for differences in financial development, I use a proxy of credit availability, measured as domestic credit extended for the private sector as a percentage of GDP (Beck *et al,* 2010).

iv. Quality of regulation. The extent to which employment protection legislation is put to practice could vary across countries, depending on the quality of enforcing and regulating institutions. Caballero *et al* (2013) and Micco and Pagés (2006) find that the efficiency of labor allocation is lower in countries where employment protection is more likely to be enforced. To account for this, I control for an indicator of regulatory quality taken from the World Bank's Governance Indicator's database.

3. DATA AND MEASUREMENT

3.1. The WBES dataset

The main data source in this paper is the World Bank's Enterprises Survey (WBES) dataset. The WBES is an ongoing project that collects firm-level data worldwide. The major advantage of the WBES dataset is that it is collected systematically using standardized survey instruments. The dataset thus provides comparable data that is unique in its extensive country coverage. Sampling for the WBES is conducted using stratified sampling procedure to ensure representative coverage. First, the number of industry groups to be covered across each major sector (services, manufacturing and non-agriculture primary activities) is determined. For manufacturing, industry grouping is based on 2-digit ISIC classification. The number of industry groups to be covered in each country is determined according to the size of the total economy which is taken as a proxy for the universe of firms. Once the number of industries to be covered is decided, the largest industry groups in the economy, in terms of contribution to output and employment, are selected.

In the second stage, a sampling equation is used to determine a representative sample size per industry group. The sample size is chosen to achieve representativeness for the proportion of plants and the average sales in the industry. Finally, further stratification is made based on firm-size and geographical location to select the plants that are covered by the survey.[10]

Data collection started in 2002 and different countries have been covered in subsequent years. Panel data is available for some countries; however, the country coverage of the panel dataset is limited. The analysis in this paper is performed using a cross-section dataset that includes the largest number of available observations for each country. When multiple years of data are available for a country, the year for which the largest number of observations are available is selected[11].

I started compiling the cross-section data by removing non- manufacturing plants, and observations with missing or incomplete data for the essential variables, i.e. sales, intermediate inputs, labor cost and net book value of capital. Similarly, loss-making plants with negative

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[10] The WBES excludes fully state owned enterprises in order to achieve comparability across countries. A full description of the sampling procedure can be found in the following website: http://www.enterprisesurveys.org/methodology/

[11] In the regression analysis, I include dummies that indicate year of data collection to capture potential differences in the economic environment across the years in which the data is collected.

value added are removed. Then I remove outliers that are potentially measured with error and hence can significantly influence the measures of misallocation. Outliers in this case are defined as the top and bottom percentiles of the marginal product of labor (MPL) and total factor revenue productivity (TFPR) within each country-industry group. In addition, I remove 30 industries for which the interquartile range for the log of MPL has values above three since the substantial dispersion suggests that data for these industries is likely to be measured with error.

Once the data is cleaned, a number of industries end up with too few valid observations compared to the original sample. To make sure that the final sample is not too far from the original sample which is designed to be representative, I exclude certain industries that have relatively small coverage. Specifically, I exclude industries with fewer than five observations, and industries that, compared to the original dataset, end up with less than half the number of observations.

I exclude from the analysis all countries that have fewer than 40 observations after cleaning, and whose sample in terms of coverage relative to the original dataset is less than 40%. While the decision for the cut-off point is rather arbitrary, it ensures the exclusion of countries for which the final dataset is not likely to be representative. This leads to a final dataset of 91 countries with a total of 29,589 plants. The analysis is conducted with a dataset of 731 industries of 2-digit level ISIC classification[12]. For measuring revenue productivity, an additional capital stock data is required, which is less frequently available. As a result, the number of countries covered for this alternative measure falls to 61 and the number of industries to 501.

Table (A1) in the Appendix presents for each country the year of data collection, the coverage of the final sample relative to the original, the number of observations, GDP per capita and summary values of labor productivity and wage rate in the dataset. As shown at the bottom of column (3), the average coverage of the final dataset is 76%, implying that about a quarter of the observations in the original sample are lost in the data cleaning process, mainly because they provide incomplete data. Column (2) shows that the average sample size across countries is 325. There is large difference in sample size across countries: whereas large countries such as India, Brazil and China have well above a thousand observations, smaller ones such as Estonia and Swaziland have only around 40 observations. The dataset covers mostly low- and middle-income countries with average per capita income of USD 3,700, ranging from Ireland (USD 49,000) to Democratic Republic of Congo (USD 125), all in current prices.

[12] Detailed ISIC codes are not available for certain industries, and thus around 5 percent of the industries in the dataset are defined at a higher level of aggregation that includes two to three 2-digit ISIC codes.

Given that micro data is subject to numerous possibilities of measurement error, it becomes necessary to ascertain the validity of the WBES dataset by comparing it with external sources. For this purpose, Table (A1) provides measures of labor productivity (value added per worker) and wage rate that are imputed from the WBES dataset, and GDP per capita in current prices. Since there are substantial differences in labor productivity and wage rate across plants in the same country, median values are used as summary statistics. Correlation results show that labor productivity, wage rate and GDP per capita are strongly correlated with coefficients above 0.90. The last two columns of Table (A1) report the ratios of the labor productivity and wage rate to GDP per capita. On average, labor productivity and wage rates are about 4.3 and 1.6 times larger than GDP per capita respectively, reflecting the high productivity of the manufacturing sector relative to the rest of the economy. The wage rate to GDP per capita ratio also has reasonable values across countries. The largest values of the ratio are in poor countries where low-productivity agricultural sectors are important, such as Democratic Republic of Congo (6.4), Afghanistan (4.8) and Kenya (4.2), whereas it is below one in many middle-income countries. Overall, the WBES dataset appears to provide reasonable values of wage rate and labor productivity relative to GDP per capita.

For measuring the marginal product of labor, I use data on total production, cost of intermediate inputs and labor inputs. Additional data for book value capital stock is used for measuring revenue productivity. Output is defined as value added, which is calculated as the difference between sales and the cost of intermediate inputs. Cost of intermediate inputs is calculated by adding up three major cost categories: energy consumption (fuel, electricity and other energy costs), cost of raw materials and overhead and other expenses. To account for differences in hours worked and human capital, labor input is measured using labor cost rather than employment. The elasticity parameter β in Equation (1) is calculated using the average share of labor in value added within each country-industry. Since β is an additive element in the log of MPL, wrongly measuring it will not have any effect on the measures of dispersion.

--- [Table 1 about here] ---

Table (1) provides correlation results between the four measures of dispersion, three alternative measures of labor productivity and the median wage rate. The Table includes the standard deviations (SD) and interquartile ranges of MPL and TFPR. LP1 and LP2 are measures of aggregate labor productivity at country level and at country-industry level respectively. Both are calculated as value added per worker in USD using data from the INDSTAT database (UNIDO, 2012). LP3 and wages respectively refer to labor productivity and wage rate at country-industry level, both calculated from the WBES dataset using median values across plants within each industry.

Firstly, the Table shows that the four measures of dispersion are strongly correlated with each other. For example, the standard deviations of (the logs of) MPL and TFPR have a large correlation coefficient of 0.62, indicating the internal consistency between the two measures of misallocation. All the four measures of dispersion also have significant negative correlation with LP1, although this correlation is not consistent for the other measures of labor productivity. However, all measures of dispersion are strongly correlated with the median wage rate, implying that misallocation is associated with lower per capita labor compensation. In general, these results suggest that larger misallocation is associated with lower productivity levels as has been shown in previous studies (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008).

Descriptive statistics given in Table (2) also show that the standard deviations of (the logs of) MPL and TFPR have large average values. In addition, both measures of dispersion have large standard deviations suggesting that the level of misallocation varies significantly across industries and countries. The average interquartile range of (the log of) MPL is almost one. This gap implies that the average ratio of MPL between the top and bottom quartiles is 2.7, implying substantial dispersions of MPL. The average interquartile range for TFPR is 1.15, suggesting that on average the revenue productivity of the top quartile is almost 3.2 times that of the bottom quartile. These large dispersions indicate the presence of significant misallocation of resources across plants that lowers aggregate productivity below the potentially achievable level.

3.2. Employment protection

In this paper, I focus on dismissal cost, which is one of the most important and widely studied aspects of employment protection. Cross-country data for dismissal cost is taken from the website of the World Bank's Employing Workers' project, which is a part of the Doing Business Indicators program.

Dismissal cost is calculated as the average number of weekly wages an employer is required to pay upon dismissing redundant employees with 1, 5 and 10 years of seniority. The cost of firing is expressed in terms of weekly wages in order to make it comparable across countries[13]. First developed by Botero *et al* (2004), this measure provides a reasonable approximation for the financial cost of firing employees. Detailed data for employees of different seniority levels is available only for 2010 and 2011, and the average value of the two years is used in this paper.

[13] Alternatively, one could use the broader alternative measure of dismissal cost that includes both severance payment and the cost of advance notice requirements. I use severance payment in this paper because it is by far the larger of the two and because it is the 'net' dismissal cost (i.e. unlike for the advance notice payment, the employer does not receive work in exchange for the severance payment). The results in this paper are robust for both ways of measuring dismissal cost.

--- [Table 2 about here] ---

Table (2) provides description results for dismissal cost and two additional indices of employment protection. Dismissal cost requirements are on average 18 weeks long, although there is substantial difference across countries. In DRC, Iraq and Uganda, there are no dismissal cost requirements whereas in Zimbabwe dismissal cost is equal to almost two years of wages (92 weeks). Sri Lanka and Indonesia have the next largest dismissal cost requirements that are slightly above one year of wages.

The two additional indices of employment protection in Table (2) measure the level of procedural burden that employers face while hiring and firing workers. These indices are important for measuring the non-financial aspects of employment protection legislation that use bureaucratic procedures for protecting employment. Higher values of *dismissal procedures* indicate that employers face greater procedural hurdles while dismissing redundant workers, for example because of approval requirements from relevant authorities and worker re-assignment obligations. Similarly, higher values of *hiring procedures* show greater burden in employment procedures such as restrictions on fixed-term contracts and on increasing working hours. Appendix B details the construction of the two indices using raw data from the World Bank's Employing Workers dataset. Correlation results between the three indicators show that only one pairwise correlation - between dismissal cost and dismissal procedures – is significant with a coefficient of 0.27. Since the variables appear to measure different aspects of employment protection, I conduct sensitivity tests by controlling for the two indices in the regression analysis.

4. BASELINE REGRESSIONS RESULTS

As indicated in the data description, the WBES is designed to give representative values for total sales and the number of plants per industry. However, around a quarter of the total observations are not available in the version of the dataset used for analysis largely because of missing data. To account for the resulting difference in data reliability across industries, I estimate all regressions with analytic weights, using as weighting variable the coverage rate i.e. the ratio of the sample size in the final dataset relative to the original dataset. This leads to the GLS estimator in which observations from industries with higher coverage are given greater weight since they are likely to have smaller variance[14].

[14] Potentially because of the limited variation in the weighting variable (which varies between 40 and 100 percent), the results are qualitatively similar when unweighted regression is used. On a related note, all regressions are estimated assuming that the standard errors could have arbitrary correlation within countries. This cluster estimator is especially appropriate for Equation (3) where country effects are not included. Even in Equations (4) & (5), accounting for clustering can account for any arbitrary

Table (3) provides the results for the specification given by Equation (3). The dependent variables are the standard deviations of the logs of MPL and TFPR within each country-industry group. Note that the number of observations falls substantially when TFPR is used due to the additional data requirement for capital stock. The results show that dismissal cost has significant positive effect on the standard deviations of both MPL and TFPR. The standard deviations of (the logs of) MPL and TFPR increase by 0.004-0.005 points when dismissal cost increases by one week of wages. This implies that an increase in dismissal cost from the 10th percentile (4.3 weeks) to the 90th percentile (27 weeks) is associated with an increase in the standard deviation of MPL by 11 percent relative to the mean (22.7*0.4/0.83). A similar increase of dismissal cost is associated with 12 percent rise in the standard deviation of TFPR.

--- [Table 3 about here] ---

Among the control variables, private domestic credit appears with a negative and significant coefficient in regression (1), indicating that a well-developed financial sector reduces misallocation. The significant positive coefficients of regulatory quality suggest that misallocation is larger in countries with better regulatory quality. This is potentially because high-quality regulatory institutions are more capable at enforcing employment protection and other legislation (Caballero *et al*, 2013; Micco and Pagés, 2006). In the next section, I conduct a sensitivity analysis with an interaction effects model to test if the effect of employment protection depends on regulatory quality.

Next, I present the results for the regression models that include interaction terms between dismissal cost and indicators of labor adjustment demand. The aim of these regressions is to test if the effect of employment protection is higher in industries with greater labor adjustment demand. The first two regressions of Table (4) are based on the specification of Equation (4) and the last two are based on Equation (5).

--- [Table 4 about here] ---

The interaction term between dismissal cost and the benchmark layoff propensity is positive and significant for the standard deviations of both MPL and TFPR. This confirms that employment protection has a larger effect on misallocation in industries that have greater demand for labor adjustment. The marginal effect of employment protection on misallocation is also large when we compare industries with different layoff rate. The standard deviation of MPL is 21 percent higher relative to its mean when we compare an industry at the 90th percentile of layoff rate in a country at the 90th percentile of dismissal cost against another

correlation between the error terms that persists in spite of the inclusion of country dummies. Finally, dummies showing year of data collection are included in all regressions since, as is shown in Table (A1), data is collected in different years across countries.

industry at the 10th percentile of layoff rate in a country at the 10th percentile of dismissal cost (1.665*10.2/0.828). The equivalent increase for the standard deviation for TFPR is 27 percent.

The last two regressions of the Table are based on Equation (5) in which industry-level sales growth rate is interacted with dismissal cost. As described earlier, dismissal cost is interacted with both sales growth rate and its squared term because labor adjustment demand is higher in expanding and shrinking industries[15]. Note that the number of observations declines significantly due to lack of sales growth data in many countries.

The interaction term between dismissal cost and the square of sales growth is insignificant for the standard deviation of MPL, but it is positive and significant for the standard deviation of TFPR. The positive coefficient in the last regression implies that the marginal effect of dismissal cost is higher in industries experiencing sales expansion and decline. Since expanding or shrinking industries are expected to have greater labor adjustment demand, this is suggestive that dismissal cost reduces labor reallocation. However, the insignificant coefficient in regression (3) casts doubt on the reliability of this result. In the next section, I consider alternative measures of labor adjustment demand to check the sensitivity of this result.

Overall, the results reported in this section attest that employment protection is associated with greater dispersion of the marginal product of labor and total factor productivity. The evidence shows that employment protection has the unintended consequence of inducing misallocation of resources, and thus lowering aggregate productivity. The effect of employment protection is also higher in industries that have greater demand for adjusting their labor inputs, implying that employment protection induces misallocation by affecting the process of labor reallocation.

5. SENSITIVITY TESTS

5.1. Data quality and model specification

In this sub-section, I provide a number of sensitivity tests to check the robustness of the baseline regression results. More specifically, I consider alternative measures of labor adjustment demand and misallocation, and check for potential omitted variable problems.

i. Alternative measures of labor adjustment demand

The results for the interaction effects models could depend on the way labor adjustment demand is measured, which calls for sensitivity tests using alternative measures of labor

[15] Out of the 370 industries for which sales growth data is available, 54 industries (around 15 percent of the total) have negative sales growth rates. This is based on sales growth data averaged over the years 2001-2010 in order to roughly match the periods of data collection for the WBES dated.

adjustment demand. The baseline estimation for Equation (4) is based on benchmark layoff propensity data from US, which arguably has the most permissive labor market in the world. It is nonetheless possible that this layoff rate data reflects institutional features of the US economy. In addition, the data could suffer from measurement error if there are mismatches in industry aggregation between the US and other countries.

Therefore, I provide sensitivity tests using two alternative benchmarks of layoff propensity. The first is a binary form of US layoff rate that classifies industries into high- and low-layoff groups using the average value across industries as cut-off point. The advantage of this measure is that it captures broad qualitative differences in layoff propensity across industries using a binary classification that is less susceptible to measurement error (Bassanini *et al*, 2009). As an alternative benchmark of layoff propensity, I use industry-level layoff rate data from the UK, another country with less constraining labor regulation. The data is again taken from Bassanini *et al* (2009) who used it for measuring the same concept of labor adjustment demand.

--- [Table 5 about here] ---

Table (5) provides the regression results for the two alternative measures of layoff propensity. In the first two regressions, the interaction term between dismissal cost and the US layoff dummy is positive and significant. This result suggests that industries with qualitatively higher layoff rate are affected more by employment protection. The last two regressions show that the interaction term between dismissal cost and layoff rate from UK are not significant, suggesting that the results are sensitive to the source of the benchmark layoff propensity. The results thus appear to depend on the assumption that the US labor market is the most competitive, which is an assumption adopted by several studies (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008).

Next, I turn to the interaction effect model with sales growth, which is the second measure of labor adjustment demand. The baseline regression for Equation (5) is based on sales growth data at country-industry level from UNIDO's database. Due to the relatively low availability of industry-level sales data in this database, there is considerable decline in the number of observations in the baseline regressions. For this reason, I use alternative proxies for sales growth.

Although the WBES dataset provides no information on sales growth rates, it includes information on whether or not the firm experienced sales growth in the past one year. As an alternative measure of sales growth, I use the proportion of firms that register sales growth within each country-industry group. An important advantage of this variable is that it refers to sales growth in the same industries for which we measure misallocation.

As a second alternative measure of sales growth among plants in the WBES dataset, I use the average size of plants in each country-industry. Generally, smaller businesses are more dynamic, in part because they tend to be young ventures and adjust their inputs through the process of learning-by-doing (Dunne *et al*, 1989). As a result, the process of job reallocation has been found to be higher among smaller firms (Haltiwanger *et al*, 2008). Therefore, the average size of plants in an industry can be used as a proxy for the magnitude of demand for labor adjustment in the industry. For measuring firm size, I take the average number of permanent employees across plants within each country-industry group.

--- [Table 6 about here] ---

Table (6) provides regression results using the proportion of plants that registered sales increase, and the average firm size in an industry. Unlike sales growth rate, these variables have a linear relationship with labor adjustment demand and thus only a linear interaction term is included in the regressions. Since labor adjustment demand is expected to be higher when the proportion of growing plants is larger and the average plant size is lower, the interaction terms involving these variables are expected to be positive and negative respectively.

From regression (1) in Table (6), the interaction term between dismissal cost and the proportion of growing plants is positive and significant. This implies that the marginal effect of employment protection is larger in industries where a bigger proportion of plants are growing. The interaction term, however, turns insignificant in regression (2) where the standard deviation of TFPR is considered. One possibility for this result could be the considerable decline in the number of observations in this regression compared to Table (3), due to lack of response for the survey question on sales growth.

Regressions (3) & (4) show that the interaction term between dismissal cost and average firm size per industry is negative and significant as expected. The marginal effect of employment protection thus declines as the average firm size of the industry increases, confirming that industries dominated by smaller firms (and thus have greater labor adjustment demand) are more severely affected by employment protection. To sum up, these sensitivity tests for the most part show that the results are robust for different ways of measuring labor adjustment demand.

<u>ii. Model specification</u>

The specifications given by Equations (4) & (5) are unlikely to suffer from omitted variable bias since country effects are included, removing any potential cross-country differences. However, the regression model of Equation (3) can suffer from omitted variable problems since several institutional factors can affect misallocation. In this sub-section, I consider two potential misspecification problems.

The first problem is that dismissal cost could capture the effects of other related aspects of employment protection that do not directly affect the cost of dismissal. Since dismissal cost is likely to be positively correlated with other aspects of employment protection such as procedural requirements, failing to control for these factors could bias the coefficients of dismissal cost upwards. Therefore, I re-estimate Equation (3) by including the two additional indices of dismissal and hiring procedures that are presented in Table 2. Secondly, the effect of employment protection on misallocation could be unequal across countries. Caballero *et al* (2013) and Micco and Pagés (2006) find that the effect of employment protection on economic outcomes tends to be higher in countries where employment protection is more likely to be enforced. To account for this, I extend Equation (3) by including an interaction term between dismissal cost and regulatory quality. If differences in law enforcement are important, the interaction term should appear positive and significant.

Table (7) provides the regression results for the two sensitivity tests. In the first two regressions, I control for the two indices measuring the stringency of dismissal and hiring procedures. Dismissal cost remains significant in both regressions, whereas the other two indices are insignificant. Thus, the financial burden of dismissing redundant workers appears to be the most important source of misallocation. This is consistent with theoretical results that confirm that dismissal cost has a strong effect on reallocation by reducing both job creation and job destruction (Lagos, 2006).

--- [Table 7 about here] ---

The last two columns of the Table report the results for the regression model that includes an interaction term between dismissal cost and regulatory quality. The interaction term is insignificant in regression (1) and weakly significant in regression (2). Overall, there is no clear evidence that the effects of employment protection increase with law enforcement in our dataset[16].

<u>iii. Alternative measures of misallocation</u>

In this sub-section, I consider using the interquartile ranges of the logs of MPL and TFPR as alternative measures of dispersion. One potential problem of using the standard deviation is that it is sensitive to outlying observations, which are likely to be measured with error. The interquartile range has the advantage of not being affected by extreme values, although it could understate the extent of misallocation since it ignores the dispersion along the top and bottom quartiles of the distribution.

[16] The results are unchanged when a more specific indicator measuring *rule of law* is used, again from the World Bank's Governance Indicators database. When included directly, both dismissal cost and rule of law have positive coefficients, but their interaction terms are overall insignificant.

The first result is presented in Table (A2) in the Appendix, which is analogous to Table (3). Dismissal cost is positive and significant in both regressions, confirming the robustness of the results to alternative ways of measuring dispersions.

Table (8) reports the sensitivity check for the interaction effects models. The first two regressions include an interaction term between dismissal cost and US layoff rate. The interaction term appears only weakly significant for MPL, and insignificant for TFPR. The interaction terms with layoff propensity thus do no

t appear robust when the interquartile range is used for measuring dispersion. This is potentially because the interquartile range fails to capture misallocation along the top and bottom quartiles.

--- [Table 8 about here] ---

The interaction term with the square of sales growth, however, appears strongly significant in both regressions. The large positive coefficients confirm that the marginal effect of employment protection is much larger in industries with large positive and negative sales growth rates. At least for this measure of labor adjustment demand, the sensitivity test confirms that the results are robust to alternative ways of measuring misallocation that are less sensitive to outlying observations.

<u>iv. Estimation on a subset of countries</u>

Although the WBES is designed to be representative, around a quarter of the total observations are lost in the data cleaning process. To make sure that the results are not driven by data that is potentially unrepresentative, I conduct a robustness test by confining the analysis to a subset of countries with relatively high data coverage.

For this purpose, I include only those countries in which the number of observations in the final dataset relative to the original dataset is at least 70 percent (as opposed to the 40 percent requirement used so far). Since only few countries have sufficient coverage for TFPR, this sensitivity test is implemented only using MPL, for which data is more widely available. In this this sub-sample, the number of valid observations declines to 525 industries in 60 countries (as opposed to 731 industries and 91 countries in the baseline regression). This significantly improves the average coverage to 85 percent and the number of observations per country to 422.

--- [Table 9 about here] ---

Table (9) provides three regression results, all using the standard deviation of MPL. Dismissal cost has a significant positive effect on the standard deviation of MPL, with an equal coefficient as in the baseline result of Table (3). The interaction term between dismissal cost and layoff rate also remains positive and significant. The interaction term of dismissal cost and the square of sales growth is positive and weakly significant. Compared to the baseline regression (3) of Table (4), the interaction term has a much larger coefficient. Overall, this test shows that the baseline regression results are not unduly driven by observations from countries with potentially low data quality.

5.2. Instrumental variable estimation

Regression analysis involving the effects of institutional variables is often subject to endogeneity problems because institutional design could be responsive to economic outcomes. In the current analysis, a potential problem is that employment protection could be strengthened following economic decline with the aim of protecting existing jobs. If low economic growth is also associated with higher misallocation, the estimates of the baseline regressions could overstate the effect of employment protection.

For sensitivity test, I conduct instrumental variable (IV) estimation by instrumenting employment protection with three historical variables. In an influential paper, Botero *et al* (2004) argue that a country's legal origin and the historical control of government power by leftist parties are important predictors of the level of employment protection in a country. They find that left power has a strong positive effect on employment protection and that civil law countries have significantly higher employment protection than common law countries. Since these variables are historical, they are also exogenous to our measures of misallocation and thus can be used as instruments for employment protection. Previous studies have similarly used these variables to instrument employment protection among OECD economies (Bassanini *et al*, 2009).

The first two instrument variables in this paper are thus a set of dummy variables showing legal origin, and a variable measuring the proportion of recent years during which leftist parties held government power. However, leftist governments are more likely to succeed in adopting pro-labor laws in authoritarian countries than in democratic countries with multi-party systems of government. For this reason, I use a third instrumental variable that measures the level of electoral competitiveness in a country. The instrumental variable regression is estimated using the three instruments as well as an interaction term of electoral competitiveness and left power to capture the likely non-linear effect of left power on labor law legislation[17].

[17] Left power and electoral competitiveness are calculated using data for the years 1975-2000 using data from the Database of Political Institutions (Beck *et al*, 2001). Electoral competitiveness is calculated using average values of two related variables that measure the competitiveness of elections in the legislative and executive branches of government between one (no legislation and elections) and 7 (at

The first stage regression of the IV estimation is reported in Table (A3) of the Appendix. The interaction term between left power and electoral competitiveness is negative and significant, revealing that the effect of left power on employment protection declines with electoral competitiveness. However, countries with English legal origin appear to have higher dismissal cost once other controls are taken into account.

Table (10) reports the two-stage least squares IV estimates for Equation (3). For this specification, the regressions are estimated using a cross-country dataset since all of the variables in the first stage regression vary only across countries. The standard deviations are calculated across all firms within a country after MPL and TFPR are log-differenced from their industry averages in order to account for heterogeneity across industries.

--- [Table 10 about here] ---

For comparison, the standard least square results using country-level data are reported in the first two columns of the Table. These regressions show that dismissal cost has positive and significant effect on the standard deviations of MPL and TFPR. The IV results are reported in the last two columns, along with results for overidentifying restrictions and exogeneity tests at the bottom rows. Importantly, the overidentifying restrictions tests do not reject the null hypotheses that the instruments are valid, confirming the instruments to be exogenous. The IV regressions also show that dismissal cost has significant positive effect on the standard deviations of both MPL and TFPR. Compared to the standard least square results, IV gives larger coefficients for dismissal cost, revealing that the baseline results are not biased upwards. If anything, the IV results suggest that that the baseline regressions might have understated the effect of employment protection. However, the standard errors for the coefficients of dismissal cost are also much larger in the IV regressions. This is in line with the results of the exogeneity tests that reject the exogeneity of dismissal cost, suggesting that OLS is a more efficient estimator.

Next, I present the IV results for Equation (4), which includes an interaction term between dismissal cost and layoff propensity. Since layoff rate are taken from exogenous sources, they can be used as instruments for themselves. Unfortunately, sales growth is likely to be correlated with any potentially omitted variables that affect both misallocation and employment protection. Given the difficulty of getting instruments for sales growth, I conduct IV estimation only for the interaction effects model involving layoff propensity.

Table (11) reports the IV results using two alternative layoff rate measures from US and UK. In these regressions, the interaction terms between dismissal cost and layoff rate are

least 25 percent seats taken are by opposition). The final indicator of electoral competitiveness is the average of the two variables.

instrumented with the interaction of the respective layoff rate and the instrumental variables (i.e. legal origin dummies, left power, electoral competitiveness, and the interaction term of the last two). Although none of the instrumental variables vary across industries, their interaction terms with layoff rate vary across industries, allowing us to conduct regression analysis using country-industry data (for a similar IV application see Bassanini *et al*, 2009).

--- [Table 11 about here] ---

The overidentifying restrictions tests at the bottom of Table (11) again do not reject the validity of the instruments. In addition, the exogeneity tests uphold that dismissal cost is exogenous. The IV results show that the interaction term between dismissal cost and US layoff rate is positive and significant. Compared to the baseline regression results in Table (4), the IV estimates of the coefficient are in general larger. The last two columns provide additional IV estimates using UK layoff rate data. The interaction term appears significant for the standard deviation of MPL, although it remains insignificant for TFPR. To sum up, results from IV estimation suggest that the baseline regression results are robust for potential endogeneity problems.

6. CONCLUSION

An emerging literature reveals that misallocation is an important determinant of aggregate productivity (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008; Bartelsman *et al*, 2013). Hence, understanding the sources of misallocation can give useful insights regarding the drivers of cross-country differences in productivity. However, there is little evidence on how institutional factors such as employment protection affect misallocation. Existing studies that analyze the effect of employment protection on aggregate productivity (Bassanini *et al*, 2009; Besley and Burgess, 2004) do not distinguish the separate effects of employment protection on misallocation since they rely on aggregate productivity data.

This study investigates the effect of employment protection on misallocation of resources across manufacturing plants. To my knowledge, this is the first study to closely study the effects of employment protection on resource misallocation across heterogeneous plants. The advantage of looking into the effect of employment protection on misallocation is that there is a clear theoretical prediction that employment protection induces greater misallocation (Hopenhayn and Rogerson, 1993; Lagos, 2006).

Following the recent literature on misallocation (Hsieh and Klenow, 2009), I rely on the within-industry dispersions of the marginal product of labor and total factor productivity as measures of misallocation. Firm-level data from the WBES dataset that covers more than 90 countries is used for this purpose. The results show that dismissal cost is associated with greater dispersion of the marginal product of labor and revenue productivity, indicating that it induces greater misallocation, thus reducing aggregate productivity and income.

Further, the analysis shows that the effect of employment protection is larger in industries with greater labor adjustment demand. More specifically, employment protection has significantly larger effect in industries with inherently larger layoff rate and in expanding and shrinking industries in terms of sales growth. Since high layoff rate and sales expansion/shrinking imply greater labor adjustment demand, these results demonstrate that employment protection induces misallocation by constraining the adjustment of labor.

A limitation of this paper that, due to the nature of the data it uses, it exclusively focuses on misallocation along the intensive margin. Previous theoretical and empirical studies have shown that employment protection can also lower aggregate productivity by reducing the entry of new firms and by serving as an exit tax, thus keeping unproductive firms in operation (Hopenhayn and Rogerson, 1993). Assessing the effect of employment protection on misallocation due to entry and exit dynamics can add further insight beyond those documented in this paper.

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FUNDING

This work was supported by a research grant from the Netherlands Organization for Scientific Research (NWO).

TABLES AND FIGURES

Table 1: Correlation and descriptive results for measures of misallocation

	SD(MPL)	SD(TFPR)	IQR(MPL)	IQR(TFPR)	LP1	LP2	LP3	Wages
SD(MPL)	1							
SD(TFPR)	0.621	1						
	0							
IQR(MPL)	0.674	0.519	1					
	0	0						
IQR(TFPR)	0.429	0.682	0.473	1				
	0	0	0					
LP1	-0.278	-0.278	-0.278	-0.211	1			
	0	0	0	0.001				
LP2	-0.055	-0.024	-0.051	0.095	0.570	1		
	0.278	0.701	0.318	0.133	0			
LP3	0.028	-0.017	0.012	-0.000	0.578	0.645	1	
	0.450	0.708	0.752	0.994	0	0		
Wage	-0.130	-0.112	-0.153	-0.094	0.650	0.615	0.880	1
	0.001	0.013	0	0.038	0	0	0	

Notes: The standard deviation (SD) and interquartile range (IQR) are calculated using log transformed values of the marginal product of labor (MPL) and total factor revenue productivity (TFPR) within each country-industry group. LP1 and LP2 are respectively country-level and industry-level measures of aggregate labor productivity (value added per worker) computed using data from INDSTAT database (UNIDO, 2012). LP3 and Wages are calculated as the median value of value added per worker and wage rate across all plants within each country-industry group. The cells indicate values of pairwise correlation coefficients and their p-values.

Table 2: Descriptive statistics

	Obs	Mean	Std. Dev.	Min	Max
A. Measures of misallocation					
SD(MPL)	731	0.828	0.330	0.128	2.44
SD(TFPR)	501	0.933	0.274	0.223	2.126
IQR(MPL)	731	0.99	0.451	0.038	2.96
IQR(TFPR)	501	1.153	0.44	0.064	2.921
B. Measures of employment protection					
Dismissal cost	91	15.915	13.957	0	92.445
Dismissal procedures index	91	2.885	2.114	0	7.000
Hiring procedures index	91	0.251	0.225	0	0.800
C: Control Variables					
Trade openness	91	82.978	35.541	27.197	199.755
FDI inflow	91	4.382	3.741	-4.653	20.254
Registration procedures to start a business	91	9.442	2.738	4.000	17.875
Private domestic credit	91	37.279	32.684	3.321	167.308
Regulatory quality	91	-0.200	0.735	-2.060	1.728

Notes: The summary statistics are calculated at country-industry level in panel A, and at country-level for panels B and C. Trade openness, FDI inflow and private domestic credit are all calculated as a percentage of GDP. All control variables are averaged over the years 2001-2010 to match the years of data collection of the WBES dataset.

Table 3: The effect of employment protection on misallocation

	(1) SD(MPL)	(2) SD(TFPR)
Dismissal cost	0.004***	0.005***
	(0.001)	(0.001)
Trade openness	0.009	-0.095
	(0.075)	(0.069)
Net FDI inflow	-0.010	-0.008
	(0.006)	(0.007)
Registration procedures	0.004	0.006
	(0.006)	(0.010)
Private domestic credit	-0.002**	-0.001
	(0.001)	(0.001)
Regulatory quality	0.179***	0.144***
	(0.034)	(0.039)
Constant	1.354***	1.268***
	(0.138)	(0.163)
Observations	731	501
R-squared	0.368	0.223

Notes: The regressions are based on Equation (3). The dependent variables are within-industry standard deviations (SD) of log-transformed values of MPL and TFPR. Country- and industry-effects and dummies showing year of data collection are included in all regressions. The standard errors given in parentheses are corrected for clustering by country. The asterisks indicate the usual levels of significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: The effect of employment protection on misallocation: interactions with labor adjustment demand

	(1) SD(MPL)	(2) SD(TFPR)	(3) SD(MPL)	(4) SD(TFPR)
Dismissal cost X US layoff rate	0.102***	0.133***		
	(0.036)	(0.035)		
Dismissal cost X (Sales growth)^2			0.019	0.095***
			(0.019)	(0.025)
Dismissal cost X (Sales growth)			-0.012	-0.025***
			(0.009)	(0.007)
Sales growth^2			-0.011	-2.151***
			(0.444)	(0.543)
Sales growth			0.259	0.753***
			(0.287)	(0.228)
Constant	1.231***	1.240***	1.806***	0.944***
	(0.037)	(0.036)	(0.043)	(0.078)
Observations	731	501	370	236
R-squared	0.602	0.481	0.635	0.517

Notes: Regressions (1) & (2) are based on Equation (4) and regressions (3) & (4) are based on Equation (5). The dependent variables are within-industry standard deviations of log-transformed values of MPL and TFPR. Country- and industry-effects and dummies showing year of data collection are included in all regressions. The standard errors given in parentheses are corrected for clustering by country. The asterisks indicate the usual levels of significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Regression results using alternative measures of layoff propensity

	(1) SD(MPL)	(2) SD(TFPR)	(3) SD(MPL)	(4) SD(TFPR)
Dismissal cost X US layoff dummy	0.002**	0.002**		
	(0.001)	(0.001)		
Dismissal cost X UK layoff rate			0.030	0.040
			(0.025)	(0.026)
Constant	1.323***	0.834***	1.303***	0.804***
	(0.024)	(0.026)	(0.029)	(0.041)
Observations	731	501	731	501
R-squared	0.600	0.471	0.598	0.469

Notes: The dependent variables are within-industry standard deviations of log-transformed values of MPL and TFPR. Country- and industry-effects and dummies showing year of data collection are included in all regressions. Standard errors given in parentheses are corrected for clustering by country. The asterisks indicate the usual levels of significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Regression results using alternative measures for sales growth

	(1) SD(MPL)	(2) SD(TFPR)	(3) SD(MPL)	(4) SD(TFPR)
Dismissal cost X Growing plants	0.010**	-0.003		
	(0.004)	(0.006)		
Dismissal cost X Size			-0.003***	-0.002***
			(0.001)	(0.001)
Share of growing plants	-0.168	-0.077		
	(0.132)	(0.181)		
Size			0.101***	0.054*
			(0.025)	(0.027)
Constant	1.154***	0.964***	1.144***	0.858***
	(0.108)	(0.053)	(0.071)	(0.067)
Observations	488	340	731	501
R-squared	0.620	0.511	0.613	0.477

Notes: The dependent variables are within-industry standard deviations of log-transformed values of MPL and TFPR. Country- and industry-effects and dummies showing year of data collection are included in all regressions. The standard errors given in parentheses are corrected for clustering by country. The asterisks indicate the usual levels of significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Regression results with additional controls

	(1) SD(MPL)	(2) SD(TFPR)	(3) SD(MPL)	(4) SD(TFPR)
Dismissal cost	0.004***	0.004***	0.004**	0.008***
	(0.001)	(0.001)	(0.002)	(0.002)
Dismissal cost x Regulatory quality			-0.000	0.002*
			(0.001)	(0.001)
Dismissal procedures	0.005	0.009		
	(0.009)	(0.008)		
Hiring procedures	-0.125	-0.107		
	(0.095)	(0.091)		
Trade openness	0.006	-0.096	0.009	-0.124
	(0.074)	(0.068)	(0.077)	(0.076)
Net FDI inflow	-0.010	-0.008	-0.010	-0.007
	(0.006)	(0.007)	(0.006)	(0.007)
Registration procedures	0.005	0.007	0.004	0.006
	(0.007)	(0.011)	(0.006)	(0.009)
Private domestic credit	-0.002***	-0.001	-0.002**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Regulatory quality	0.190***	0.155***	0.180***	0.101**
	(0.033)	(0.036)	(0.044)	(0.050)
Constant	1.366***	1.264***	1.355***	1.222***
	(0.159)	(0.197)	(0.140)	(0.166)
Observations	731	501	731	501
R-squared	0.374	0.231	0.368	0.234

Notes: The dependent variables are within-industry standard deviations of the logs of MPL and TFPR. Country- and industry-effects and dummies showing year of data collection are included in all regressions. The standard errors given in parentheses are corrected for clustering by country. The asterisks indicate the usual levels of significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Interaction effect regression results using the interquartile range

	(1) IQR(MPL)	(2) IQR(TFPR)	(3) IQR(MPL)	(4) IQR(TFPR)
Dismissal cost X Layoff rate	0.085*	0.078		
	(0.050)	(0.054)		
Dismissal cost X (Sales growth)^2			0.145***	0.197***
			(0.052)	(0.057)
Dismissal cost X (Sales growth)			-0.058**	-0.045***
			(0.022)	(0.013)
Sales growth^2			-2.046	-5.074***
			(1.277)	(1.426)
Sales growth			1.173	1.575***
			(0.704)	(0.458)
Constant	1.603***	1.670***	1.187***	1.345***
	(0.059)	(0.056)	(0.061)	(0.122)
Observations	731	501	370	236
R-squared	0.437	0.333	0.547	0.428

Notes: Regressions (1) & (2) are based on Equation (4) and regressions (3) & (4) are based on Equation (5). The dependent variables are within-industry interquartile ranges (IQR) of log-transformed values of MPL and TFPR. Country- and industry-effects and dummies showing year of data collection are included in all regressions. The standard errors given in parentheses are corrected for clustering by country. The asterisks indicate the usual levels of significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Regression results using a subset of the dataset with higher coverage rate

	(1) SD(MPL)	(2) SD(MPL)	(3) SD(MPL)
Dismissal cost	0.004***		
	(0.001)		
Dismissal cost X Layoff rate		0.114***	
		(0.031)	
Dismissal cost X (Sales growth)^2			0.058*
			(0.030)
Dismissal cost X (Sales growth)			-0.018**
			(0.009)
Sales growth^2			-0.842
			(0.695)
Sales growth			0.436
			(0.337)
Trade openness	0.047		
	(0.086)		
Net FDI inflow	-0.017*		
	(0.009)		
Registration procedures	0.007		
	(0.007)		
Private domestic credit	-0.002***		
	(0.001)		
Regulatory quality	0.243***		
	(0.039)		
Constant	1.338***	1.204***	1.759***
	(0.176)	(0.034)	(0.048)
Observations	525	525	230
R-squared	0.411	0.662	0.742

Notes: The regressions are, respectively, based on Equations (3), (4) & (5). The dependent variable is the within-industry standard deviation of the log of MPL. Country- and industry-effects and dummies showing year of data collection are included in all regressions. The standard errors given in parentheses are corrected for clustering by country. The asterisks indicate the usual levels of significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Instrumental variable regression results: main effect analysis

	(1) SD(MPL)	(2) SD(TFPR)	(3) SD(MPL)	(4) SD(TFPR)
Dismissal cost	0.005***	0.005***	0.009**	0.006**
	(0.001)	(0.001)	(0.004)	(0.003)
Trade openness	-0.011	0.011	0.017	0.017
	(0.098)	(0.093)	(0.095)	(0.081)
Net FDI inflow	-0.012*	-0.015	-0.012*	-0.015
	(0.007)	(0.012)	(0.007)	(0.010)
Registration procedures	0.014	0.030*	0.015*	0.033**
	(0.009)	(0.016)	(0.008)	(0.013)
Private domestic credit	-0.002	-0.001	-0.002*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Regulatory quality	0.244***	0.205***	0.269***	0.213***
	(0.046)	(0.048)	(0.048)	(0.053)
Constant	1.334***	1.192***	1.250***	1.138***
	(0.164)	(0.257)	(0.151)	(0.219)
Observations	91	61	90	60
R-squared	0.585	0.587	0.551	0.587
Chi2 overid. test: P-value			0.986	0.768
Chi-sq exogeneity test: P-value			0.166	0.665
Estimator	OLS	OLS	IV	IV

Notes: All regressions are based on Equation (3). The standard deviations are calculated across the whole economy after MPL and TFPR are log-differenced from their industry averages. For example, SD(MPL) is calculated using log(MPLsi/MPLs) where MPLsi is firm-level MPL and MPLs is its industry average. The instruments in the IV regressions are left power, electoral competitiveness, the interaction term of the two, and legal origin dummies. Dummies showing year of data collection are included in all regressions. Analytic weights are used in all regressions, using the relevant country-level coverage rate as a weight. Estimation is based on 2-stage least square and robust standard errors are given in parentheses. The asterisks indicate the usual levels of significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Instrumental variable regression results: interaction effects model

	(1) SD(MPL)	(2) SD(TFPR)	(3) SD(MPL)	(4) SD(TFPR)
Dismissal cost X US layoff rate	0.233***	0.149**		
	(0.083)	(0.067)		
Dismissal cost X UK layoff rate			0.146**	0.049
			(0.065)	(0.052)
Constant	1.124***	1.224***	1.151***	1.287***
	(0.098)	(0.075)	(0.100)	(0.077)
Observations	722	494	722	494
R-squared	0.598	0.484	0.591	0.475
Chi2 overid. test: P-value	0.603	0.514	0.735	0.464
Chi-sq exogeneity test: P-value	0.089	0.661	0.067	0.813

Notes: The regressions are based on Equation (4). The instrumental variables are the interaction terms between the respective layoff rate variable and the instrumental variables, namely left power, electoral competitiveness, the interaction term of the two, and legal origin dummies. Country- and industry-effects and dummies showing year of data collection are included in all regressions. Estimation is based on 2-stage least square and robust standard errors are given in parentheses. The asterisks indicate the usual levels of significance: *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX A

Table A1: Data coverage and other summary statistics by country

	Country	(1) Year	(2) Obs	(3) Coverage	(4) LP, median	(5) Wages, Median	(6) GDP pc, 2005	(7) LP-GDP pc ratio	(8) Wage-GDP pc ratio
1	Afghanistan	2008	65	53	3,582	995	210	17.09	4.75
2	Algeria	2002	257	61	3,936	2,120	3,112	1.26	0.68
3	Angola	2006	195	92	4,742	2,688	1,857	2.55	1.45
4	Argentina	2010	616	77	22,586	11,578	4,736	4.77	2.44
5	Armenia	2009	51	45	4,259	1,201	1,598	2.66	0.75
6	Azerbaijan	2009	80	67	3,325	1,424	1,578	2.11	0.90
7	Bangladesh	2007	1,242	96	1,171	500	429	2.73	1.17
8	Belarus	2008	49	47	7,263	2,340	3,090	2.35	0.76
9	Belize	2010	50	69	20,351	7,299	3,821	5.33	1.91
10	Benin	2004	127	87	3,155	972	562	5.62	1.73
11	Botswana	2006	81	71	4,441	1,866	5,468	0.81	0.34
12	Brazil	2003	1,476	90	4,826	2,480	4,743	1.02	0.52
13	Bulgaria	2007	562	88	7,990	2,519	3,733	2.14	0.67
14	Burkina Faso	2009	59	62	7,896	1,040	385	20.52	2.70
15	Burundi	2006	93	91	1,513	583	154	9.82	3.79
16	Chile	2010	604	77	23,110	9,686	7,631	3.03	1.27
17	China	2003	1,290	80	14,353	1,330	1,731	8.29	0.77
18	Colombia	2010	598	84	13,855	6,228	3,404	4.07	1.83
19	Congo, DR	2006	134	90	1,878	832	125	14.99	6.64
20	Costa Rica	2005	252	73	9,866	6,855	4,633	2.13	1.48
21	Cote d'Ivoire	2009	158	76	2,686	995	908	2.96	1.10
22	Croatia	2007	343	83	30,572	11,547	10,090	3.03	1.14
23	Dominican Rep.	2010	83	68	10,093	4,086	3,670	2.75	1.11
24	Ecuador	2006	291	74	12,403	3,833	2,751	4.51	1.39
25	Egypt	2004	776	79	1,424	640	1,209	1.18	0.53
26	El Salvador	2003	414	89	3,980	2,870	2,825	1.41	1.02
27	Eritrea	2009	42	45	4,906	504	245	20.04	2.06
28	Estonia	2009	54	59	30,271	12,785	10,330	2.93	1.24
29	Ethiopia	2002	199	47	940	500	165	5.68	3.02
30	Georgia	2008	50	41	3,104	1,297	1,470	2.11	0.88
31	Ghana	2007	284	97	1,138	610	496	2.29	1.23
32	Guatemala	2003	364	84	3,896	2,699	2,140	1.82	1.26
33	Guinea	2006	124	92	820	331	325	2.53	1.02
34	Guyana	2004	144	88	4,150	2,082	1,105	3.75	1.88
35	Honduras	2003	371	82	2,561	1,965	1,412	1.81	1.39
36	Hungary	2009	68	59	22,745	7,688	10,937	2.08	0.70
37	India	2002	1,609	88	3,477	865	732	4.75	1.18
38	Indonesia	2009	802	68	1,806	857	1,258	1.44	0.68

	Country	(1) Year	(2) Obs	(3) Coverage	(4) LP, median	(5) Wages, Median	(6) GDP pc, 2005	(7) LP-GDP pc ratio	(8) Wage-GDP pc ratio
39	Iraq	2011	422	89	12,229	3,885	1,135	10.78	3.42
40	Ireland	2005	119	68	75,334	31,095	48,866	1.53	0.64
41	Jamaica	2010	91	75	11,201	4,915	4,179	2.68	1.18
42	Kazakhstan	2009	121	66	5,462	2,470	3,771	1.45	0.66
43	Kenya	2007	381	96	8,770	2,211	526	16.67	4.20
44	Kyrgyz Republic	2003	85	83	772	394	476	1.62	0.83
45	Lao PDR	2009	98	67	1,856	873	475	3.90	1.84
46	Latvia	2009	64	70	16,200	6,583	6,973	2.32	0.94
47	Lithuania	2009	51	50	15,312	6,580	7,604	2.01	0.87
48	Macedonia, FYR	2009	67	53	7,520	3,349	2,937	2.56	1.14
49	Madagascar	2009	141	69	2,093	767	282	7.43	2.72
50	Malawi	2005	124	79	2,600	590	215	12.10	2.75
51	Malaysia	2002	632	70	14,308	4,311	5,499	2.60	0.78
52	Mali	2007	279	93	1,790	898	403	4.45	2.23
53	Mauritania	2006	61	76	2,426	1,601	717	3.38	2.23
54	Mauritius	2009	180	83	7,372	2,501	5,054	1.46	0.49
55	Mexico	2010	1,002	86	13,190	5,345	7,973	1.65	0.67
56	Moldova	2003	93	90	1,330	661	831	1.60	0.80
57	Mongolia	2009	104	80	2,041	1,045	991	2.06	1.05
58	Morocco	2004	724	86	4,935	3,313	1,931	2.56	1.72
59	Mozambique	2007	304	90	1,676	836	317	5.29	2.64
60	Namibia	2006	76	72	12,128	3,531	3,491	3.47	1.01
61	Nepal	2009	95	69	1,486	774	298	4.99	2.60
62	Nicaragua	2003	400	88	1,853	1,307	1,166	1.59	1.12
63	Nigeria	2007	920	97	2,472	973	803	3.08	1.21
64	Pakistan	2002	707	81	3,238	936	691	4.69	1.35
65	Panama	2006	152	63	12,652	4,231	4,776	2.65	0.89
66	Paraguay	2010	86	51	12,642	4,309	1,267	9.98	3.40
67	Peru	2010	586	77	14,145	4,869	2,881	4.91	1.69
68	Philippines	2009	697	71	6,269	1,525	1,205	5.20	1.27
69	Poland	2009	58	42	20,328	6,644	7,963	2.55	0.83
70	Romania	2009	78	41	7,010	3,486	4,572	1.53	0.76
71	Russia	2009	358	51	12,748	4,771	5,337	2.39	0.89
72	Rwanda	2006	46	78	1,797	966	281	6.40	3.44
73	Senegal	2007	247	95	2,782	1,502	800	3.48	1.88
74	Serbia	2009	92	68	14,598	5,449	3,391	4.30	1.61
75	Slovenia	2009	69	66	49,813	23,118	17,855	2.79	1.29
76	South Africa	2007	647	95	16,768	7,747	5,234	3.20	1.48
77	Spain	2005	106	79	54,531	22,873	26,056	2.09	0.88

	Country	(1) Year	(2) Obs	(3) Coverage	(4) LP, median	(5) Wages, Median	(6) GDP pc, 2005	(7) LP-GDP pc ratio	(8) Wage-GDP pc ratio
78	Sri Lanka	2004	324	72	1,267	624	1,242	1.02	0.50
79	St. Lucia	2010	48	76	11,306	6,944	5,529	2.04	1.26
80	Suriname	2010	65	87	13,009	8,928	3,593	3.62	2.48
81	Swaziland	2006	58	83	6,720	1,954	2,540	2.65	0.77
82	Tajikistan	2003	89	93	802	343	358	2.24	0.96
83	Tanzania	2006	246	90	2,883	845	375	7.69	2.25
84	Thailand	2004	1,309	95	5,857	1,795	2,644	2.22	0.68
85	Trinidad & Tobago	2010	83	71	16,992	8,567	12,231	1.39	0.70
86	Turkey	2008	523	58	30,581	7,683	7,088	4.31	1.08
87	Uganda	2006	278	91	1,542	838	325	4.75	2.58
88	Uruguay	2010	210	55	19,883	7,992	5,252	3.79	1.52
89	Vietnam	2005	1,088	95	1,608	811	642	2.50	1.26
90	Zambia	2007	289	95	3,826	1,517	626	6.11	2.42
91	Zimbabwe	2011	359	95	.	.	458	.	.
	Minimum		*42*	*41*	*772*	*331*	*125*	*0.81*	*0.34*
	Maximum		*1,609*	*97*	*75,334*	*31,095*	*48,866*	*20.52*	*6.64*
	Median		*158*	*77*	*4,921*	*2,101*	*1,731*	*2.74*	*1.22*
	Mean		*325*	*76*	*9,737*	*3,920*	*3,705*	*4.27*	*1.55*

Notes: Labor productivity (LP), GDP per capita, and wages are all expressed in USD.

Table A2: The effect of dismissal cost on alternative measures of misallocation

	(1) IQR(MPL)	(2) IQR(TFPR)
Dismissal cost	0.002**	0.004**
	(0.001)	(0.002)
Trade openness	-0.083	-0.125
	(0.079)	(0.080)
Net FDI inflow	-0.009	-0.008
	(0.009)	(0.009)
Registration procedures	0.006	0.005
	(0.011)	(0.015)
Domestic sector credit	-0.003***	-0.001
	(0.001)	(0.001)
Regulatory quality	0.188***	0.105*
	(0.046)	(0.053)
Constant	1.479***	1.569***
	(0.192)	(0.236)
Observations	731	501
R-squared	0.211	0.149
Unit of analysis	Country	Country

Notes: The regressions are based on Equation (3). The dependent variables are the within-industry interquartile ranges (IQR) of log-transformed values of MPL and TFPR. Industry- and country- effects and dummies showing year of data collection are included in all regressions. The standard errors are given in parentheses are corrected for clustering by country. The asterisks indicate the usual levels of significance: *** p<0.01, ** p<0.05, * p<0.1.

Table A3: First stage regression results for the indicators of employment protection

	(1) Dismissal cost
Left Power X Electoral Competitiveness	-0.075***
	(0.023)
Left Power	0.401***
	(0.132)
Electoral Competitiveness	4.103*
	(2.080)
English legal origin	11.067**
	(4.439)
French legal origin	5.692
	(3.482)
Trade openness	-0.034
	(0.040)
Net FDI inflow	-0.453*
	(0.272)
Registration procedures	0.096
	(0.522)
Private domestic credit	0.019
	(0.069)
Regulatory quality	-4.227
	(3.902)
Constant	-16.757
	(11.336)
Observations	90
R-squared	0.348

Note: Data for left power and electoral competitiveness, is taken from the Database of Political Institutions compiled by Beck *et al* (2001), and are based on the years 1975-2000. Robust standard errors are given in parenthesis. The asterisks indicate the usual levels of significance: *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX B

Measuring dismissal and hiring procedures indices

The dismissal and hiring procedures indices are calculated using country-level data from the 'Employing Workers' project of the Doing Business Indicators program conducted by the World Bank. The methodology used for calculating the indices follows closely the official methodology of calculating employment protection indicators[18]. Separate indices are calculated for the years 2010 and 2011 which are the only years for which detailed data is available. The final analysis is conducted using the average value of the indices over the two years.

Dismissal procedures index: Higher values of this index indicate heavier regulatory burden for dismissing redundant workers. The index is calculated using responses for the following eight questions. (1) Is it legal for an employer to terminate the employment contract of a worker on the basis of redundancy? (2) Must the employer notify a third party before dismissing one redundant worker? (3) Does the employer need the approval of a third party in order to dismiss one redundant worker? (4) Must the employer notify or consult a third party prior to a collective dismissal (at least 9 employees)? (5) Must the employer obtain prior approval from a third party before a collective dismissal (at least 9 employees)? (6) Is there a re-training or re-assignment obligation before an employer can make a worker redundant? (7) Are there priority rules that apply to redundancy dismissals or layoffs? (8) Are there priority rules applying to re-employment?

The responses for these questions are coded as follows. If the response for question 1 is no, dismissal due to redundancy is illegal implying the highest level of dismissal restriction. In this special case the final *dismissal procedures index* is assigned the maximum possible value of 10 and all the other questions are not used. For every other question except question (4), if the answer is yes, a score of 1 is assigned; otherwise a score of 0 is given. An answer of yes to question (4) is given a score of 2, thus giving a greater weight for this response. The final index is calculated as the sum of responses for questions (2)-(8) except for the case where the response of question 1 is no (in which case it takes a value of 10).

Hiring procedures index: Higher values of this index indicate heavier burden of employment regulation. The index is calculated using responses for the following five questions. (1) Are fixed-term contracts prohibited for permanent tasks? (2) What is the maximum allowed cumulative duration of a fixed-term employment contracts (in months), including all renewals? (3) Can the workweek for a single worker extend to 50 hours per week (including overtime) for 2 months each year to respond to a seasonal increase in production? (4) Are there restrictions on night work? (5) Are there restrictions on "weekly holiday" work?

A response of yes for question (1) is assigned a value of 1, whereas a response of no is assigned 0. For question (2) a score of 1 is assigned if the maximum cumulative duration of fixed term contracts is less than 3 years; 0.5 if it is 3 years or more but less than 5 years; and 0 if fixed-term contracts can last 5

[18] http://www.doingbusiness.org/methodology/employing-workers

years or more. For questions (3)-(5) a response of yes is assigned a score of 0, whereas a score of 1 is assigned if the answer is no. The final *hiring procedures index* is calculated as the average of the five variables.